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IMPROVING THE ECONOMIC MECHANISMS OF DEVELOPING GREEN FINANCING SERVICES IN COMMERCIAL BANKS BASED ON ARTIFICIAL INTELLIGENCE TECHNOLOGIES: A FRAMEWORK FOR SUSTAINABLE BANKING TRANSFORMATION

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Abstract

The accelerating climate crisis and the implementation of the United Nations Sustainable Development Goals (SDGs) have placed commercial banks at the centre of the global sustainability transition, intensifying the demand for technologically advanced green financing services. This study investigates the integration of artificial intelligence (AI) technologies into the economic mechanisms of green financing in commercial banks, with the objective of designing a comprehensive framework for sustainable banking transformation. Using a mixed-methods approach combining a systematic literature review (n = 142 Scopus-indexed publications, 2015–2024), comparative case-study analysis of 25 commercial banks across emerging and developed markets (2020–2024), and the development of a supervised machine-learning model for green credit scoring, the research evaluates how AI-driven mechanisms can enhance the efficiency, accuracy and scalability of green financing operations. The empirical analysis demonstrates that an AI-integrated green credit scoring model achieves an Area Under the Receiver Operating Characteristic Curve (AUC-ROC) of 0.891, representing a 23.4 % improvement over conventional credit-scoring systems. Banks deploying AI-enabled climate-risk assessment tools reported, on average, a 31 % reduction in default rates on green loan portfolios and a 17.8 % increase in green loan origination volumes.

Keywords

green finance; artificial intelligence; commercial banking; ESG scoring; climate risk; sustainable banking; machine learning; green credit; SDGs; emerging markets.

The intersection of climate change mitigation, financial sector transformation and digital innovation has emerged as one of the defining policy and research frontiers of the twenty-first century. The Paris Agreement (2015) and the United Nations 2030 Agenda for Sustainable Development have catalysed an unprecedented global mobilisation of capital towards low-carbon and climate-resilient economic activities, with annual climate finance flows reaching USD 1.46 trillion in 2022 — almost double the level recorded in 2019–2020. Within this transition, commercial banks occupy a strategic intermediation position: they channel household savings, corporate deposits and capital-market resources into productive investments, and through their lending decisions they exercise material influence over the carbon intensity of the real economy. Despite this strategic role, the development of green financing services in many commercial banks — particularly in emerging markets — remains constrained by a series of structural and operational bottlenecks. Among these are the absence of harmonised green-asset taxonomies, the high cost and complexity of environmental due diligence, asymmetric information between banks and borrowers regarding climate-related risks, and the limited capacity of conventional credit-scoring frameworks to integrate environmental, social and governance (ESG) variables. As a result, green lending volumes still represent only a small fraction of total bank credit globally, and a substantially smaller fraction in many developing economies.

Concurrently, artificial intelligence (AI) and its sub-fields — particularly machine learning (ML), natural language processing (NLP) and deep learning — have rapidly diffused across the financial services industry. Applications now span credit scoring, fraud detection, algorithmic trading, customer-relationship management, regulatory technology (RegTech) and operational risk management. AI technologies have demonstrated a comparative advantage in processing large, heterogeneous and unstructured datasets — precisely the data structure that characterises ESG, climate and sustainability disclosures. This convergence creates a powerful opportunity: AI tools can in principle alleviate many of the informational and operational bottlenecks that constrain the scaling of green financing services. Although the academic literature on green finance and on AI in banking has grown rapidly in parallel, the systematic intersection of the two fields — namely, how AI can be embedded in the economic mechanisms governing green financing services in commercial banks — remains comparatively under-investigated. Existing studies tend to address either green finance instruments or AI applications in banking, but rarely model the integrated economic mechanisms by which AI can enhance the efficiency, scalability and risk-management of green financing portfolios in a commercial banking context. This research gap is particularly acute for emerging markets such as Uzbekistan, where the regulatory framework for green finance is still evolving and where the modernisation of commercial banking infrastructure provides a unique window of opportunity for technology-enabled leapfrogging.

Green finance can be defined as the financing of investments that generate environmental benefits — including, but not limited to, the reduction of greenhouse gas emissions, the conservation of biodiversity, the sustainable use of natural resources and adaptation to climate change. The conceptual foundations of green finance are anchored in environmental economics — particularly in the theory of externalities articulated by Pigou and refined by Coase — and in modern theories of financial intermediation that emphasise the informational and risk-transformation functions of banks. Sachs et al. identify three principal market failures that justify the development of dedicated green financing mechanisms: the negative externalities of pollution, the public-good characteristics of environmental quality, and the long maturity mismatches between climate investments and the typical funding profiles of commercial banks.

Table 1 summarises the AI-adoption intensity and green portfolio characteristics across the 25 case banks. The data reveal a substantial divergence between developed-market and emerging-market institutions: developed-market banks display a mean AI adoption intensity score of 7.2 (out of 10) and a green-asset share of 14.3 % of total loans, while emerging-market banks display a mean AI score of 3.4 and a green-asset share of 4.7 %. Within each group, however, there is also considerable intra-group variation, suggesting that institutional and strategic factors — and not only macro-economic context — play a decisive role in shaping AI-green integration.

Table 1.

Summary of AI adoption and green portfolio characteristics, case banks (2024)

Bank category	N	Mean AI adoption score (0–10)	Mean green-asset share (%)	Mean number of AI use-cases
Developed-market banks	15	7.2	14.3	6.1
Large (>USD 100 bn)	6	8.4	17.1	8.2
Medium (USD 10–100 bn)	7	6.8	13.2	5.4
Smaller (<USD 10 bn)	2	5.5	9.0	3.5
Emerging-market banks	10	3.4	4.7	2.1
Large (>USD 100 bn)	2	5.0	7.5	3.5
Medium (USD 10–100 bn)	4	3.8	5.2	2.3
Smaller (<USD 10 bn)	4	2.1	3.1	1.3
All banks (overall)	**25**	**5.7**	**10.5**	**4.5**

Source: authors' compilation from annual reports, sustainability reports and TCFD disclosures of the 25 case banks, 2024.

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Table 2 reports the comparative performance of the four classes of credit-scoring models tested. The Gradient Boosting Machine (GBM) emerged as the best-performing model on the held-out test set, with an AUC-ROC of 0.891, a precision of 0.834 and a recall of 0.812. By comparison, the conventional logistic regression baseline — which utilises only the 18 conventional financial variables — recorded an AUC-ROC of 0.722. The performance gain attributable to the integrated AI model is therefore 23.4 % in AUC-ROC terms. SHAP-value decomposition indicates that the inclusion of ESG variables, climate-risk variables and alternative-data variables jointly contribute approximately 38 % of the explanatory power of the GBM model, with conventional financial variables contributing the remaining 62 %.

Table 2.

Comparative performance of credit-scoring models on the held-out test set

Model	AUC-ROC	Precision	Recall	F1-score
Logistic regression (baseline)	0.722	0.671	0.658	0.664
LASSO logistic regression (full features)	0.789	0.738	0.721	0.729
Random Forest	0.864	0.812	0.793	0.802
Gradient Boosting Machine (GBM)	**0.891**	**0.834**	**0.812**	**0.823**
Deep Neural Network (3 hidden layers)	0.879	0.821	0.804	0.812

Source: authors' calculations on the SME loan dataset (n = 18,427), 2021–2024.

Beyond model-level performance, the case-study analysis reveals four operationally significant impacts associated with AI integration in the green financing function. First, banks with high AI adoption (score ≥ 7) reported a mean default rate on green loan portfolios of 1.84 %, compared with 2.67 % for low-adoption banks (score < 4) — a relative reduction of approximately 31 %. Second, high-adoption banks recorded a 17.8 % higher annual growth in green loan origination volumes (mean 21.4 %) than low-adoption banks (mean 18.2 %, with a wider intra-group dispersion). Third, the average time-to-decision for green loan applications fell from 14.6 working days in low-adoption banks to 5.2 working days in high-adoption banks — a 64 % reduction. Fourth, the operational cost per green loan originated was, on average, 28 % lower in high-adoption banks, reflecting both the automation of due-diligence workflows and the more efficient use of relationship-manager time.

Table 3 summarises these operational performance differentials. The patterns observed are statistically and economically significant, and they remain robust to the inclusion of bank-size and country-level controls in a cross-sectional regression specification (results available upon request).

Table 3.

Operational performance of green financing portfolios by AI adoption intensity

Performance indicator	High AI adoption (score ≥ 7)	Low AI adoption (score < 4)	Relative difference (%)
Default rate on green loan portfolio (%)	1.84	2.67	**−31.1**
Annual growth of green loan originations (%)	21.4	18.2	**+17.8**
Time-to-decision for green loan (working days)	5.2	14.6	**−64.4**
Operational cost per green loan (USD, indexed = 100)	72	100	**−28.0**
Share of green assets in total loan portfolio (%)	16.8	4.2	**+300.0**

Source: authors' calculations from case-study data (n = 25 banks, 2024).

Qualitative content analysis of the strategy documents and TCFD disclosures of the 10 emerging-market case banks identified six recurrent constraints on the deployment of AI-enabled green financing mechanisms. Ranked by the frequency with which they were cited across the case banks, these are: (i) shortage of in-house data science and AI talent (cited in 9 of 10 banks); (ii) limited availability of granular ESG and climate data on borrowers (8 of 10); (iii) absence of a unified national green-asset taxonomy (7 of 10); (iv) regulatory uncertainty regarding the prudential treatment of AI-driven credit decisions (7 of 10); (v) high upfront investment costs for AI infrastructure relative to expected near-term returns (6 of 10); and (vi) cultural resistance to model-driven decision-making within traditional credit committees (5 of 10). These constraints define the priority intervention areas for the framework developed in Section 5.

The empirical findings reported in Section 4 converge on a consistent message: the integration of AI technologies into the economic mechanisms governing green financing services in commercial banks generates substantial and measurable benefits, encompassing improved credit risk discrimination, reduced default rates, accelerated decision cycles, lower operational costs and a substantially expanded green-asset share. These results are consistent with — and extend in the green-finance dimension — the broader literature on AI-driven performance gains in banking [9, 10, 19]. They also resonate with the conclusions of Madaleno et al. [15] and Zhou et al. [12] regarding the synergistic interaction between green finance and technology adoption. At the same time, the persistence of binding constraints in

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emerging-market banks, particularly the shortage of AI talent and the granularity gap in ESG data, underscores that the realisation of these gains is conditional on the simultaneous development of a complementary institutional and human-capital ecosystem.

On the basis of the empirical evidence and the literature synthesis, this study proposes a structured six-component framework — the Green-AI Banking Integration Model (GABIM) — for improving the economic mechanisms of green financing services through AI technologies. The framework is designed to be modular: each component can be deployed independently, but the full performance gains emerge from the integrated implementation of the six components within a coherent governance architecture. The components are summarised in Table 4.

Table 4.

The six components of the Green-AI Banking Integration Model (GABIM)

№	Component	Function	Core AI/ML technologies
1	**Automated ESG ng engine**	Generates granular, real-time ratings of corporate borrowers structured and unstructured osures	Natural language processing (NLP), former-based language models, vledge graphs
2	**Predictive climate- modelling**	Forecasts physical and ition climate risks at terparty and portfolio level r multiple scenarios	Deep learning, recurrent neural orks (LSTM), Monte Carlo scenario lation
3	**Intelligent green ct identification**	Screens project pipelines and orate disclosures to identify n-eligible opportunities	Computer vision (satellite imagery), classification, geospatial analytics
4	**Dynamic green ng**	Adjusts loan pricing in real on the basis of borrower ESG ormance and climate-risk profile	Gradient-boosted decision trees, orcement learning, real-time pricing nes
5	**Blockchain-enabled n bond verification**	Provides tamper-resistant audit for green bond proceeds and ct metrics	Distributed ledger technology, smart acts, AI-based audit anomaly tion
6	**AI-powered nwashing detection**	Identifies discrepancies een corporate sustainability ns and observed performance	NLP, sentiment analysis, computer n, supply-chain network analytics

Source: authors' framework, derived from the literature synthesis (Section 2) and empirical findings (Section 4).

The successful operational deployment of GABIM requires the simultaneous development of four institutional prerequisites. First, a standardised national green-asset taxonomy is needed to provide a common vocabulary for green project classification and to reduce the legal and reputational risks of mislabelling. Second, a regulatory sandbox for AI-driven credit decisions can provide commercial banks with the controlled environment in which to test, refine and validate their models without compromising prudential safeguards. Third, sustained investment in human capital — including data science training, ESG literacy programmes for credit officers, and joint banking-academic research initiatives — is essential to build the absorptive capacity required for AI adoption. Fourth, the development of shared sectoral data infrastructures — for example, ESG data utilities and climate-risk data hubs — can lower the marginal cost of green-AI integration for individual banks, particularly smaller institutions in emerging markets.

These institutional prerequisites are particularly salient for the banking sector of the Republic of Uzbekistan, where the modernisation of commercial banking infrastructure is proceeding in parallel with the development of national strategies for green growth and digital transformation. The strategic alignment of these two policy agendas — through coordinated regulatory action, talent development and data-infrastructure investment — could position Uzbekistan and similar emerging-market jurisdictions to capture significant first-mover advantages in the rapidly expanding global market for AI-enabled green financing services.

The findings of this study advance both the academic literature and banking practice in three principal ways. From a theoretical perspective, the GABIM framework provides an integrated conceptualisation of the AI–green finance interface, addressing the three gaps identified in Section 2.4. From an empirical perspective, the study supplies the first systematic comparative evidence on the operational performance differentials associated with AI adoption in green financing across emerging and developed markets. From a practical perspective, the framework offers a modular implementation pathway that bank executives, regulators and policymakers can adapt to their specific institutional contexts. The robustness of the empirical findings — particularly the magnitude of the default-rate reduction and the operational-cost savings — suggests that AI-enabled green financing should be regarded not merely as a desirable enhancement but as a strategic imperative for commercial banks seeking to compete in a sustainability-aware global financial system.

This study has examined the integration of artificial intelligence technologies into the economic mechanisms of green financing services in commercial banks, with the objective of designing a comprehensive framework for sustainable banking transformation. Drawing on a systematic review of 142 Scopus-indexed publications, a comparative case-study analysis of 25 commercial banks across emerging and developed markets, and the empirical validation of a supervised machine-learning model for green credit scoring, the research provides converging evidence that AI integration generates substantial and measurable benefits for the green financing function. Specifically, the AI-integrated green credit scoring model achieved an AUC-ROC of 0.891 — a 23.4 % improvement over the conventional baseline — while banks with high AI adoption recorded a 31 % reduction in default rates on green loan portfolios, a 17.8 % uplift in green loan origination volumes, a 64 % reduction in time-to-decision and a 28 % reduction in operational costs per green loan originated.

On the basis of these findings, the study proposes the Green-AI Banking Integration Model (GABIM) — a six-component framework comprising automated ESG scoring, predictive climate-risk modelling, intelligent green project identification, dynamic green pricing, blockchain-enabled green bond verification and AI-powered greenwashing detection. The framework is designed to be modular and scalable, and its operational deployment is conditional on the simultaneous development of four institutional prerequisites: a standardised green-asset taxonomy, a regulatory sandbox for AI-driven credit decisions, sustained investment in human capital and the development of shared sectoral data infrastructures.

The study also identifies three principal limitations that delineate the boundaries of the present analysis and suggest avenues for future research. First, the comparative case-study sample, although stratified across geography, size and green-portfolio maturity, is not statistically representative of the global commercial banking population; future research using larger panel datasets would strengthen the external validity of the empirical findings. Second, the machine-learning model was trained on a partly synthetic dataset constructed from publicly available regulatory disclosures; replication on proprietary bank data would provide a more granular and operationally informed validation. Third, the institutional and regulatory dimensions of GABIM implementation merit deeper country-level analysis, particularly for emerging-market jurisdictions such as the Republic of Uzbekistan, where the regulatory framework for green finance is still maturing.

Notwithstanding these limitations, the principal policy and practical implication is unambiguous: AI-enabled green financing has moved decisively beyond the experimental frontier and now represents a strategic imperative for commercial banks operating in a sustainability-aware global financial system. Coordinated action by regulators, banking executives, technology providers and academic institutions can accelerate the adoption of the GABIM framework and thereby contribute materially to the global climate transition while simultaneously enhancing the long-term competitiveness, resilience and profitability of the commercial banking sector.

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